Assessment of Color and Infra-Red Images using No-Reference Image Quality Metrics

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***Abstract*— Image quality measures to analyze the quality of color and infra-red images acquired at various time instants of the day (morning, noon, evening) are discussed in detail with sufficient statistical results. Images are captured once every 30 minutes all through one day and night. It is observed that color images are efficient only under good lighting conditions with responses to metrics being abrupt during dawn and dusk, whereas IR images are influenced to a certain extent by illumination and contain sufficient information even under less favorable conditions. IR responses to metrics are consistent throughout day and night as expected. It is presumed that this analysis would be helpful in deriving a weighting factor that can be used in the fusion of EO and IR images.**

Keywords- Image quality measures, Image processing, Infrared images, image quality metrics

I. INTRODUCTION

A prototype Enhanced Vision System (EVS) has been developed at MSDF lab, CSIR-NAL, to demonstrate its capabilities during adverse weather conditions. It has two cameras operating in visual and infrared spectrums. An experiment was planned to come up with a weighting factor that can play a vital role in the fusion process of EO and IR images. The prototype EVS system was used to capture images across the day every 30 minutes. Image quality evaluation metrics are then used to evaluate these acquired images to develop a scheme as to which sensor would be more appropriate for a given time in a day.

Image quality assessment is a vital task in image processing applications. A statistical quality analysis of color and Infra-red images using no-reference image quality metrics are studied in this paper. Static images (without any moving objects) captured simultaneously using EO (Electro-Optical) and IR (Infra-Red) sensors, at an interval of 30 minutes since 11 hrs to 6.30 hrs the subsequent day, are used for the study. EO sensor provides a color image and IR sensor provides a gray image of the scene. A total of 80 images, 40 each for color and gray images are analyzed statistically using metrics like histogram, contrast, entropy, luminance, signal to noise ratio, spectral activity, spatial frequency etc. The impact of lighting conditions and other environmental factors for each image at various time instants are also discussed.

Image quality is a characteristic of an image that measures the image degradation/deviation, compared to an ideal or perfect image [1]. Image quality depends on four factors: how much the image formation process of the camera deviates from the pinhole model, the quality of the image measurement process, the coding artifacts that are introduced in the image and also some external environmental conditions like illumination, clouds, day/night conditions etc.

II. IMAGE QUALITY ASSESSMENT TECHNIQUES

Image Quality Measures [2,3] are figures of merit used for the evaluation of images. All proposed quality measures can be divided into two general classes:

- Subjective evaluation
- Objective evaluation

Subjective evaluation of image quality is oriented on Human Vision System (HVS). Subjects view a series of reproduced images and rate them based on the visibility of the artifacts. The subjective quality measurement, Mean Opinion Score (MOS) has been used for many years.

The importance of objective quality metric methods cannot be underestimated [4]. There are several techniques and metrics that can be measured objectively and automatically evaluated by a computer program. Therefore, they can be classified as Full-Reference (FR) or Bivariate method and No-Reference (NR) or Univariate method. In FR image quality assessment methods [5], the quality of a test image is evaluated by comparing it with a reference image that is assumed to have perfect quality. NR metrics try to assess the quality of an image without any reference to the original one.

Subjective tests are tedious, time consuming, expensive and the results depend very much on the observer. In fact, only the display quality is being assessed. Therefore, objective measures that accurately predict subjective rating are indispensable. In this report, *No-Reference* objective image quality measures for color and Infra-red images are studied and discussed.

III. No-Reference Image Quality Metrics

Image quality cannot be quantified completely by a single metric. Some of the basic image characteristics used to assess image quality [6] is as follows:

- **Brightness** - Brightness is related to the illumination system, as how light or dark is the image.
- **Clarity** – Clarity demonstrates if the image is blurred or well-defined.
- **Resolution** - Resolution is related to the numerical aperture of the objective camera lens (the higher the numerical aperture, the better the resolution) and the wavelength of light passing through the lens (the shorter the wavelength, the better the resolution). It indicates how close two points can be in the image before they are no longer seen as two separate points.
- **Contrast** - Contrast is related to the illumination system, specifying the difference in lighting between adjacent areas of the image.

Based on the above image characteristics, several No-Reference quality metrics are discussed in the following section for the study of color and infra-red image quality.

A. *Image histogram*

An image histogram is a graphical representation of the pixel distribution in a digital image. It plots the number of pixels for each pixel value. By looking at the histogram for a specific image, a viewer will be able to judge the entire pixel distribution at a glance.

The horizontal axis of the graph represents the pixel variations, while the vertical axis represents the number of pixels available for that particular pixel value. The left side of the horizontal axis represents the black and dark areas, the middle represents medium grey and the right hand side represents light and pure white areas. Thus, the histogram for a very bright image with few dark areas and/or shadows will have most of its data points on the right side and center of the graph. Conversely, the histogram for a very dark image will have the majority of its data points on the left side and center of the graph.

B. *Average Entropy*

Entropy [8,9] is a statistical measure of randomness, which can be used to characterize the texture of the input image. Information entropy denoted by H for a gray image is:

$$H = -\sum_{k=0}^{255} p(r_k)\log_2 p(r_k) \qquad (1)$$

$$p(r_k) = \frac{n_k}{n},\ k = 0,1,2,...,255$$

Where n_k denote the number of times that the k^{th} gray level appears in the image and n is the number of pixels in the image

Information entropy for a color image is the average of Information entropies of three color components Red, Blue and Green as given below:

$$H_{avg} = \sqrt{\frac{H_R^2 + H_G^2 + H_B^2}{3}} \qquad (2)$$

Where, H_R = entropy of the red component

H_B = entropy of the blue component

H_G = entropy of the green component

An image with the ideal equalization histogram possesses the maximal entropy of 8 bit. The entropy of an image with one gray value equals to zero. Therefore, higher average entropy value is a sign of better image quality.

C. *Average Contrast*

Contrast [8,9] is a visual characteristic that makes an object or its representation in an image distinguishable from other objects and the background. In visual perception, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view.

$$C_{avg} = \frac{1}{(M-1)(N-1)}\sum_{x=1}^{M-1}\sum_{y=1}^{N-1}\left|\vec{C}(x,y)\right| \qquad (3)$$

Where, M and N represent the number of rows and columns in the image respectively.

For an IR image, the contrast is the gradient calculated for the image as a single component:

$$\left|\vec{C}(x,y)\right| = \sqrt{\nabla^2 I(x,y)} \qquad (4)$$

$$\nabla I(x,y) = \frac{\partial I(x,y)}{\partial x}\hat{i} + \frac{\partial I(x,y)}{\partial y}\hat{j} \qquad (5)$$

Where, ∇ is the gradient operator and $I(x,y)$ is the Image pixel value at (x,y).

Average gradient reflects the clarity of an image. It measures the spatial resolution in an image i.e. larger average gradient indicates a higher resolution. So, higher value of Average Contrast is an indication of better image quality.

For a color image, the color contrast is given by the average of gradients of Red, Green and Blue considered individually as follows:

$$\left|\vec{C}(x,y)\right| = \sqrt{\frac{\nabla^2 R(x,y) + \nabla^2 G(x,y) + \nabla^2 B(x,y)}{3}} \quad (6)$$

D. *Average Luminance*

Luminance [8] describes the amount of light that passes through, or is emitted from a particular area, and falls within a given solid angle. It indicates how much luminous power will be perceived by an eye looking at the surface from a particular angle of view. Luminance is thus an indicator of how bright the surface will appear.

$$L_{avg} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y) \quad (7)$$

Images with higher luminance value denote more brightness in the image.

For a color image,

$$L_{avg} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} \frac{R(x,y)+G(x,y)+B(x,y)}{3} \quad (8)$$

E. *Signal to Noise Ratio*

Signal-to-noise ratio (often abbreviated SNR or S/N) is a measure used to quantify how much a signal has been corrupted by noise. Signal-to-noise ratio is sometimes referred to, as the ratio of signal (meaningful information) to background noise (false or irrelevant data).

An alternative definition of SNR is as the reciprocal of the coefficient of variation, i.e., the ratio of mean to standard deviation of a signal or measurement, useful only for variables that are always positive. Thus it is commonly used in image processing, where the SNR of an image is usually calculated as the ratio of the mean pixel value to the standard deviation of the pixel values over a given neighborhood.

$$SNR = \frac{\mu}{\sigma} \quad (9)$$

Where, μ is the mean pixel value and σ denotes the standard deviation of pixel values. SNR value less than five indicates 100% certainty in identifying image details.

F. *Metrics based on Co-occurrence Matrix*

Co-occurrence characteristics are used to calculate the spatial relationship of pixels in an image, by creating a GLCM. GLCM is the Gray Level Co-occurrence Matrix or a Gray Level Spatial Dependence Matrix that is found by calculating how often a pixel with gray-level value (grayscale intensity) i occurs horizontally adjacent to a pixel with value j. Each element of i, j in GLCM specifies the number of times that the pixel with value i occurred horizontally adjacent to a pixel with value j. MATLAB function *graycomatrix* is used to create a GLCM with an offset value of [0 1] and number of levels is eight. An Offset value of [row offset, column offset] specifies the relationship or offset, of a pair of pixels. Row offset is the number of rows between the pixel of interest and its neighbor and column offset is the number of columns between the pixel of interest and its neighbor. An offset value of [0 1] indicates horizontal relationship among the pixels at a distance of 1 pixel. Number of levels specify the number of gray levels to use when scaling the grayscale values. NumLevels of 8 scales the gray image such that, they are integers between 1 and 8. Hence, GLCM becomes an 8x8 matrix. Subsequently, the following four metrics viz., Contrast, Correlation, Energy and Homogeneity are calculated from GLCM, using the function *graycoprops*.

F1. *Image Contrast*

Image Contrast returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. For 8 levels GLCM, it ranges from zero to $(8-1)^2$.

$$C_{img} = \sum_{i=1}^{8}\sum_{j=1}^{8} |i-j|^2 g(i,j) \quad (10)$$

Where, i, j are the pixel values in the GLCM and $g(i,j)$ denotes the element of GLCM at (i,j).

F2. *Correlation*

Correlation returns a measure of how correlated a pixel is to its neighbor over the whole image. The range of correlation is between -1 to 1. Correlation is 1 or -1 for a perfect positively or negatively correlated image.

$$C_{corr} = \sum_{i=1}^{8}\sum_{j=1}^{8} \frac{(i-\mu i)(j-\mu j)g(i,j)}{\sigma_i \sigma_j} \quad (11)$$

F3. *Energy*

Energy returns the sum of squared elements in the GLCM. It is also known as uniformity, uniformity of energy or angular second moment. The energy lies between zero and one.

$$E = \sum_{i=1}^{8}\sum_{j=1}^{8} g(i,j)^2 \quad (12)$$

F4. *Homogeneity*

Homogeneity is a condition in which all the constituents are of the same nature. In image processing, Homogeneity returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal i.e. if all the pixels in a block are within a specific dynamic range. The range homogeneity is from zero to one. Homogeneity is 1 for a diagonal GLCM.

$$I_{\hom} = \sum_{i=1}^{8}\sum_{j=1}^{8} \frac{g(i,j)}{1+|i-j|} \quad (13)$$

G. *Spatial Frequency*

Spatial frequency is a characteristic of any structure that is periodic across position in space [10,11]. The spatial frequency is a measure of how often sinusoidal components (as determined by the Fourier transform) of the structure repeat per unit of distance.

The Row Frequency of an image is given by:

$$RF = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=2}^{N}[I(x,y) - I(x,y-1)]^2} \quad (14)$$

Column Frequency is defined as:

$$CF = \sqrt{\frac{1}{MN}\sum_{y=1}^{N}\sum_{x=2}^{M}[I(x,y) - I(x-1,y)]^2} \quad (15)$$

Spatial Frequency is the square root of sum of squares of row and column frequencies given as:

$$SF = \sqrt{RF^2 + CF^2} \quad (16)$$

Higher value of Spatial Frequency indicates good quality.

H. Spectral Activity Measure

Spectral Activity Measure evaluates a picture quality [11]. It is a function of Discrete Fourier Transform of an image. The Fourier transform is a representation of an image as a sum of complex exponentials of varying magnitudes, frequencies, and phases. A discrete transform is a transform whose input and output values are discrete samples, making it convenient for computer manipulation. DFT is a specific kind of discrete transform, used for Spectral analysis.

$$SAM = \frac{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}|F(x,y)|^2}{\left[\prod_{x=1}^{M}\prod_{y=1}^{N}|F(x,y)|^2\right]^{\frac{1}{MN}}} \quad (17)$$

Where, $F(x,y)$ denotes discrete Fourier transform (DFT) of an image I. Spectral Activity Measure can range from 0 to ∞. Higher values imply higher predictability.

IV. RESULTS AND DISCUSSIONS

Four test datasets containing EO and IR images were used for the study. First set S1 corresponds to a set of images (without any moving objects), captured simultaneously using EO and Infra-Red sensors. A total of 80 images taken at an interval of 30 minutes from 11 hrs to 6.30 hrs of subsequent day forms the first set. Second set S2 corresponds to a general scene obtained in the noon, third set S3 relates to an early morning scene and the fourth set S4 corresponds to that of an evening time with rain.

A. Analysis of Test Dataset-S 1

General observation made from the response of IR and color images (Figs.1&2) to various metrics indicate the following:

Color: Based on the response of images to various metrics, the color images can be grouped into four different classes:

a) Images acquired in broad daylight – 11 hrs to 18 hrs.
b) Images in the absence of natural light, but influenced by artificial lights in the surroundings – 18.30 hrs to morning 2 hrs.
c) Images in the absence of natural as well as artificial lights – 2.30 hrs to 5 hrs.
d) Images captured during sunrise – 5.30 hrs to 6.30 hrs.

Images of class (a) and (d) are good quality images with good contrast, illumination, brightness etc due to good lighting conditions. Images corresponding to class (c) are low contrast, less illuminated images due to absence of lights. Images corresponding to class (b) are also low contrast images, but a little illuminated by the artificial lights in the background.

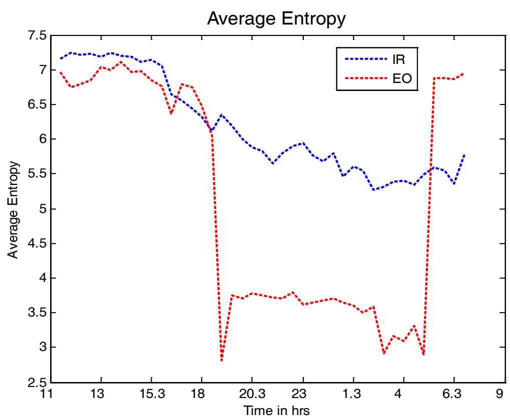


Fig.1 Average Entropy values for IR and EO of Set S1

IR: Based on the response of IR images to different quality metrics, they can be broadly grouped into three different classes:

a) Images captured when the objects and background are hot – 11 hrs to 20 hrs.
b) Images obtained when the earth begins to cool down – 20.30 hrs to 5.30 hrs.

c) Images obtained when the earth begins to heat up due to sunrays – 6 hrs onwards.

Images of class (a) are good quality images with better contrast (hot objects with good contrast and brightness; cold objects with low contrast and less brightness). Images pertaining to class (b) are low contrast images, as almost all the objects are cold at that point of time. Images corresponding to class (c) are of medium quality with average contrast and brightness due to moderate heat in the objects.

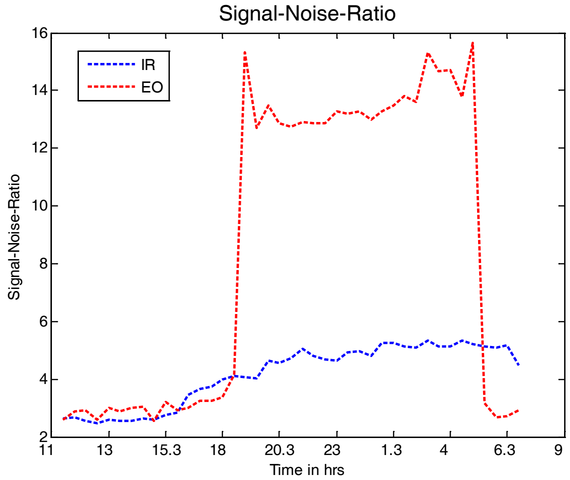
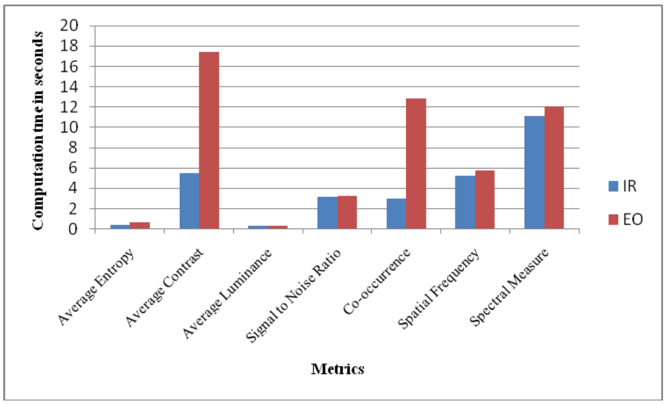


Fig.2 SNR values for IR and EO of Set S1



The time taken in seconds for each metric corresponding to IR and EO of set S1 are shown in Fig-3. Some metrics like Average Contrast, Co-occurrence etc have very high computation times for EO when compared to IR. The huge difference in time for average contrast is due to the fact that gradient is calculated thrice for EO – individually for components: red, blue and green, whereas it is only once for IR. The larger time taken for Co-occurrence metric in EO is for the conversion of RGB to gray format while calculating GLCM. In IR, there's no need for a gray conversion. On the whole, the computation time taken by all metrics for EO is comparatively high when compared to those of IR.

B. Analysis of Test Datasets- S2 to S4

From the metric values of Table.1, it is observed that color images are good only when they are exposed to good illumination (natural or artificial lights), whereas infra-red images have good information content all through day and night.

Fig.4 EO image of S4 (evening with rain)

TABLE 1: Metric values for EO and IR of datasets S2, S3 and S4

Metrics	Metric Values (S2,S3,S4)					
	Noon		Morning		Evening rain	
	EO	IR	EO	IR	EO	IR
H_{avg}	6.68	6.296	4.545	5.5609	6.2115	5.977
C_{avg}	3.48	1.345	0.693	0.8925	1.9527	0.786
L_{avg}	79.46	73.9680	62.88	73.613	84.563	58.80
SNR	2.691	2.0794	7.804	4.8389	4.9329	2.360
C_{img}	0.108	0.0366	0.010	0.0189	0.0658	0.024
C_{corr}	0.951	0.9883	0.841	0.9502	0.9245	0.983
E	0.304	0.5049	0.927	0.7615	0.4234	0.404
I_{hom}	0.948	0.9832	0.998	0.9916	0.9675	0.988
SF	5.639	3.4681	1.271	1.9735	3.5837	1.989
SAM	2277	6203.4	16909	14470	8465.5	7364

Fig.5 IR image of S4 (evening with rain)

Figs – 4 & 5 prove that IR image has been affected to a certain level by rain (due to objects cooling down). Figs 6 & 7 corresponding to EO and IR of the same scene indicate that IR has good information content (trees and vehicles visible) even in the absence of lights, when compared to that of color.

Fig.6 EO image of S3 (early morning scene)

V. CONCLUSION

Efficient, less complex and less-memory consuming image quality measures to analyze the quality of color and infra-red images acquired at various time instants are discussed in detail with sufficient statistical results. Color and Infra-red images captured once every 30 minutes all through one day and night, are used for the study. It is observed that color images are efficient only under good lighting conditions (responses to metrics being abrupt during dawn and dusk), whereas IR images are influenced to a certain extent by illumination and contain sufficient information even under less favorable conditions (responses to metrics being consistent throughout day and night), as expected. Hence it can be inferred that, EO sensors produce good quality images only during day light i.e. in the presence of good illumination, but IR sensors are capable of generating better images all through day and night. This image quality study has been implemented in MATLAB® with adequate test images.

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Fig.7 IR image of S3 (early morning scene)

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